

MODERN FUZZY MIN MAX NEURAL NETWORKS FOR PATTERN CLASSIFICATION

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ABSTRAK

Kebelakangan ini, terdapat tumpuan yang mendalam terhadap kaedah pengkomputeran lembut bagi mengatasi masalah dunia sebenar yang kompleks. Rangkaian neural dan logik kabur merupakan antara kaedah pengkomputeran lembut yang sering digunakan dalam bidang klasifikasi corak. Dalam membina sebuah model pengelas yang berkesan, para penyelidik memperkenalkan model hibrid yang menggabungkan kedua-dua logik kabur dan rangkaian neural buatan. Antara algoritma yang diperkenalkan, algoritma rangkaian neural Min-Max Kabur (FMM) terbukti sebagai salah satu rangkaian neural terulung dalam mengatasi masalah klasifikasi corak. FMM mempunyai pelbagai fitur penting, berkebolehan untuk menyediakan proses pembelajaran dalam talian dan menangani masalah kelupaan. Namun sedemikian, algoritma ini turut menghadapi beberapa batasan, khususnya dalam proses pembelajarannya, iaitu proses pengembangan, proses ujian bertindih dan proses pengecutan. Oleh itu, rangkaian neural Min-Max Kabur Moden (MDFMM) diperkenalkan dengan tujuan mengatasi batasan-batasan FMM asal. MDFMM membawa kepada beberapa sumbangan seperti mengubah suai fungsi pengaktifan pengembangan FMM asal dan menggantikannya dengan Min-Max Kabur Tertingkat (EFMM) untuk menyingkirkan kes bertindih. Pertama, kajian ini mencadangkan kaedah pengembangan baru untuk mengatasi masalah kelonggaran dan ketaksamaan pengembangan hiperboks yang bertindih. Akibatnya, kaedah ini dapat mengurangkan proses pengecutan. Kedua, kajian ini mengusulkan satu formula ujian bertindih baru yang mempermudah proses ujian bertindih FMM/EFMM dengan meliputi semua kes bertindih yang mungkin dengan sempurna. Ketiga, kajian ini mencadangkan satu proses pengecutan baru yang memberikan gambaran hiperboks yang lebih tepat dan menghindari masalah herotan data (kehilangan maklumat hiperboks). Keempat, kajian ini mengusulkan strategi ramalan baru dalam fasa ujian dengan menyepadukan persamaan jarak bersama fungsi keahlian untuk menangani masalah pembuatan keputusan rawak. Strategi ini dapat membantu untuk memberikan ramalan yang lebih tepat ketika sampel input mempunyai nilai kesesuaian yang sama dengan kelas lain. Bagi mengatasi kerumitan struktur rangkaian MDFMM, satu penambahbaikan diperkenalkan dengan meningkatkan pemilihan hiperboks yang menang dalam proses pengembangan menggunakan algoritma k-terdekat. Model cadangan baru dinamakan sebagai MDFMM-Kn. Prestasi MDFMM dan MDFMM-Kn dinilai menggunakan pelbagai set data tanda aras UCI dan set data kecerdasan buatan 2D. Di samping itu, tiga kaedah analisis statistik, iaitu kaedah bootstrap, pengesahsahihan silang k-fold dan ujian taraf bertanda Wilcoxon, digunakan untuk menyatakan kuantiti prestasi secara statistik. Berdasarkan penilaian empirik, MDFMM yang dicadangkan didapati lebih baik berbanding model sedia ada (rangkaian neural Min-Max Kabur Ubah Suai, atau MFMMN) dari segi ketepatan dengan peratusan peningkatan sebanyak 35.42%. Tambahan pula, prestasi purata MDFMM-kn berbanding model FMM dan MDFMM menunjukkan prestasi yang lebih baik dari segi kerumitan dengan peratusan sebanyak 62%.

ABSTRACT

In the recent years, the world has demonstrated an increasing interest in soft computing techniques to deal with complex real world problems. Neural network and fuzzy logic are considered to be one of the most popular soft computing techniques that applied in pattern classification domain. To build an efficient classifier model, researchers have introduced hybrid models that combine both fuzzy logic and artificial neural networks. Among these algorithms, Fuzzy Min Max (FMM) neural network algorithm has been proven to be one of the premier neural networks for undertaking the pattern classification problems. Although the FMM has many important features with the ability to provide online learning process and can handle the forgetting problem, it suffers from a number of limitations, especially in its learning process i.e., expansion process, overlapping test process, and contraction process. Therefore, Modern Fuzzy Min Max neural network is introduced with aim of overcoming the specified limitations of the original FMM. The MDFMM introduces a number of contributions in addition to modify the original FMM expansion activation function by replace it with that from the Enhanced Fuzzy Min Max (EFMM) to eliminate the overlapping cases. First, this study proposed a new expansion technique to overcome both overlap leniency and irregularity of hyperbox expansion problems, as a result, reducing the number of contraction processes. Secondly, proposing a new overlapping test formula that simplify the FMM/EFMM overlap test process with perfectly covers all the possible overlapped cases. Thirdly, proposing a new contraction process that provides more accurate hyperboxes description and avoid data distortion problem (hyperbox information losses). Fourthly, proposing a new prediction strategy in the test phase by integrating the distance equation with membership function in order to solve the randomization decision making problem, which helps to provide more accurate prediction when input sample has same fitness values with different classes. To overcome the network structure complexity of MDFMM, a further improvement is introduced by improving the selection of the winning hyperbox during the expansion process using the k-nearest neighbours algorithm (MDFMM-Kn). The performance of MDFMM and MDFMM-Kn was evaluated using different UCI benchmark datasets and 2D artificial intelligence dataset. Furthermore, three statistical analysis techniques, namely, bootstrap method, k-fold cross-validation and the Wilcoxon signed-rank test, were utilized to statistically quantify the performances. From the empirical evaluation, the proposed MDFMM is better than the recent existing model modified FMM network (MFMMN) in terms of accuracy at an improvement percentage of 35.42%. Furthermore, the average performance of the MDFMM-Kn against the FMM and MDFMM models is better than that of the existing techniques in terms of complexity at a percentage of 62%.

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LIST OF SYMBOLS

θ	User defined expansion parameter
Δ	Value of overlap
γ	Sensitive parameter

LIST OF ABBREVIATIONS

AFMN	Adaptive Fuzzy Min Man Neural
AI	Artificial Intelligence
ANN	Artificial Neural Network
ART	Adaptive Reasoning Theory
CLN	Classify Neuron
CNN	Containment Compensation Neuron
DCFMM	Data Core Fuzzy Min Max Neural Network
EFC	Inclusion/Exclusion Fuzzy Classifier
EFMM	Enhanced Fuzzy Min Max
EGFMM	Enhanced General Fuzzy Min Max
ES	Evolutionary Strategies
FAM	Fuzzy ARTMAP
FMCN	Fuzzy Min Max Compensatory neurons
FL	Fuzzy Logic
FMM	Fuzzy Min Max
MFMM-GA	Modified Fuzzy Min Max – Genetic Algorithm
FMM-KN	Fuzzy Min Max- Key Nearest
FNN	Fuzzy Neural Network
GA	Genetic Algorithm
GFMM	General Fuzzy Min Max
GP	Genetic Programming
GRFMN	General Reflex Fuzzy Min Max Neural
MDFMM	Modern Fuzzy Min Max
MDFMM-Kn	Modern Fuzzy Min Max Enhanced Key Nearest
M-FMCN	Modified- Fuzzy Min Max Compensatory neural
MFMM1	Modified Fuzzy Min Max 1
MFMM2	Modified Fuzzy Min Max 2
MFMM-GA	Modified Fuzzy Min Max with genetic algorithm
MFMMN	Modified Fuzzy Min Max Neural Network
MLF	Multilevel Fuzzy
MLP	Multi-Layer Perceptron

NFS	Neuro Fuzzy Systems
OCN	Overlap Compensation Neuron
OCR	Optical Character Recognition
PR	Pattern Recognition
RBFN	Radial Basis Function Network
SLP	Single Layer Perceptron
WFMM	Weighted Fuzzy Min Max

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